CREDIT MARKET STRUCTURE AND BANK SCREENING. AN INDIRECT TEST ON ITALIAN DATA

Mariarosaria Agostino[*], Francesca Gagliardi[**] and Francesco Trivieri[*§]

[*]*Department of Economics and Statistics, University of Calabria, Italy*

[**]*University of Hertfordshire Business School, UK*

ABSTRACT

Based on a large panel of Italian SMEs, this paper focuses on the relationship between firms' default probability and the amount of bank debt they obtain, evaluating whether and to what extent this link is affected by the degree of competition characterizing the local credit market where firms operate. Using a dynamic panel estimator, we find that higher bank competition implies a stronger influence of firms' riskiness on bank financing to SMEs. We provide two plausible interpretations of this finding: one resorting to more accurate screening by more competitive banks; the other alleging lower market power of incumbent banks, which may restrict their willingness to finance riskier firms.

JEL code: D40; G21.

Keywords: credit market structure; small and medium sized firms; bank debt; firm riskiness.

[§] Corresponding author. Department of Economics and Statistics, cubo 1-C, University of Calabria, 87036 Rende, Cosenza, Italy. Tel. +39 0984 492452, Fax +39 0984 492421, email: francesco.trivieri@unical.it.

We are grateful to two anonymous referees for their helpful comments and suggestions which helped to improve the paper. We also thank editor Mukherjee. The usual disclaimer applies.

1. INTRODUCTION

In the last decade an intense dispute in the economic literature has been centered on the question "is competition among banks good or bad?". As Cetorelli (2001) claims, the need for such a debate would be unjustified if banks' role were simply to intermediate between supply and demand of credit. In that case, in fact, there would not be reasons to treat banks differently from other firms or to doubt that market power in credit markets is likely to lead to welfare losses, as asserted by the common wisdom. However banks perform other crucial functions in an economy, such as the screening of investment projects and, through this, the allocation of capital resources to the best social uses. Understanding how credit market structure may affect these additional banks' functions represents the meaning and focus of the banking competition debate.

So far, studies on this topic have reached controversial results – on both theoretical and empirical grounds – thus calling for further research. This paper aspires to contribute to the empirical literature on banking competition by indirectly investigating the impact of credit market structure on banks' screening activity. More precisely, we focus on the relationship between default probability and bank debt at firm level and question if and to what extent this link is influenced by the degree of banking competition characterizing the local credit market in which firms operate. Our hypothesis may be stated as follows: if competition in credit markets affects banks' probability to screen – as shown, both theoretically and empirically, by several contributions in the literature on bank market structure, briefly reviewed in the next section – then it is reasonable to suppose that firms' riskiness (which is the core of bank screening) should have, *ceteris paribus*, a different effect both on the cost and quantity of credit to entrepreneurships, depending on the degree of bank competition. Since we lack information on loans interest rates at firm level, our hypothesis is investigated considering the relationship going from firms' default probability to their bank debt. We do not posit any *a priori* expectation on the sign of this relationship (thus leaving it to be an empirical finding) – since the theoretical implications of firms' characteristics, such as default risk, on lending volumes are not univocal (i.e. Stiglitz and Weiss, 1981 *versus* de Meza and Webb, 1987; for a wide discussion on this debate see Cressy, 2002).

To carry out the empirical analysis, we focus on Italian small and medium sized manufacturing firms (henceforth SMEs), which have little access to capital markets (either public equity or bond market) and are bound to ask credit from banks with branches in the same local market where they operate. Indeed, as Cesarini (2003) highlights, once internal funds are depleted, the banking channel is often the only way for Italian SMEs – usually facing high costs in employing arm's length finance (bond and Stock Exchange markets finance) – to gain access to external funds.

Consistently with other contributions on the Italian banking system, we define 103 local markets corresponding to the existing administrative provinces. This disaggregation enables us to take advantage of an important feature of the Italian case. Indeed, Italian provinces are characterized by diversity in banking structures and this provides sufficient cross-sectional variability within a single institutional framework. Given this regulatory uniformity, there is no need to control for different regimes (Bonaccorsi di Patti and Dell'Ariccia, 2004).

To measure banking competition in local credit markets, we employ the Herfindahl-Hirschman Index (HHI) on deposits which "represents a good proxy for competition in loan markets if the empirical investigation involves firms that largely borrow from local markets, that is if credit markets are local for the firms under consideration" (Petersen and Rajan, 1995 p. 418). As claimed above, this is the case for our sample units.

The indicators of firms' default probability used in this paper have been computed by Moody's KMV on our sample data, via *RiskCalc* model. As argued by Moody's KMV, this model enables high precision and accuracy in evaluating private firm credit risk by using financial statements and, for listed firms, equity market-based information. The *RiskCalc* model is adopted by leading Italian banks as a benchmark for their internal credit risk estimates. In the empirical investigation we employ the cumulative EDF (Expected Default Frequency) measures – which are actual firms' default probabilities – within one, three and five years.

The econometric analysis, implemented on a large set of micro-data running up to 2003 from 1995, is carried out by employing the dynamic panel estimator of Arellano and Bover (1995) and

Blundell and Bond (1998), which allows to take into account the role of firm-specific effects (unobserved heterogeneity), as well as the 'endogeneity' of a number of bank debt determinants.

Our results seem to indicate that higher competition in local credit markets implies a stronger influence of firms' riskiness on the amount of bank debt granted to small and medium entrepreneurships (as well as on their bank debt growth). So that, since the relationship between firms' riskiness and bank debt is found negative, *ceteris paribus*, bank financing tends to be lower for riskier SMEs running in more competitive credit markets. In our view, a plausible interpretation of this evidence is that – as argued also by other contributions (i.e. Benfratello et al, 2006) – competitive pressures might force banks to perform more accurate screening, thus raising their efficiency in funds allocation. However, bank financing to riskier firms could be lower in more competitive credit markets for a reason unrelated to bank screening: higher bank competition may reduce the market power of incumbent banks, hence lowering their willingness to finance riskier firms – an explanation in line with Petersen and Rajan's (1995) findings. As we argue below (see section 5), both these interpretations may be considered likewise plausible, as well as not conflicting with each other, since the conceptual mechanisms they subtend may jointly represent the source of our evidence.

The remainder of the paper is organized as follows. The next section presents a brief review of the literature on the economic effects of banking competition. Section 3 illustrates the econometric specification and the methodology adopted. Section 4 describes the data. Section 5 reports the results obtained and the robustness checks performed. Finally, Section 6 summarizes and concludes.

2. A BRIEF LITERATURE REVIEW

In a decade or so of debate on banking competition a considerable body of research has been proposed. Given the scope of our work, in what follows we focus briefly only on the most relevant contributions that have analyzed – both theoretically and empirically – the effects of banking competition on banks' screening activity or, more generally, the role of banking market structure on funds allocation in the economy.[1]

In a model of bank screening, Shaffer (1998) shows that the average creditworthiness of a bank's pool of borrowers declines as banking competition increases. In a similar model, Cao and Shi (2001) prove that a more intense banking competition can reduce banks' screening incentives, so that the number of banks actively performing screening and competing in credit supply falls. As a result, in a market with many banks, loan rates would be higher and credit volumes lower than in a market with a few banks. In line with this study, Dell'Ariccia (2000) concludes that more banking competition reduces the likelihood that banks will screen entrepreneurs, as opposed to indiscriminate lending.

Using a dynamic model of capital accumulation, Cetorelli (1997) points out that a monopolistic credit market brings about a trade-off between efficient allocation of funds and quantity of credit made available. A monopolist bank can efficiently screen potential borrowers, thus increasing the quality of credit supply. On the other hand, the rent-extraction behavior of the monopolist bank produces a negative effect on equilibrium credit quantities. Cetorelli and Peretto (2000) identify the same trade-off in a Cournot oligopoly model.

Chiesa (1998) claims that when banks engage in information production about firms, a concentrated banking industry leads credit allocation to be closer to the first-best optimum. Similarly, Gehrig (1998) shows that – when banks use screening procedures that generate (imperfect) information on borrowers – an increased competition reduces screening efforts, so that the quality of the overall loan portfolio declines. Also Marquez (2002), Gehrig and Stenbacka (2001), and Hauswald and Marquez (2006) argue that competition reduces banks' screening ability by worsening the pool

[1] As a consequence, we do not discuss the many studies analyzing the role of banking competition on credit availability to firms or on some other economic aspect, such as capital accumulation, growth etc. For an extensive review of these contributions see Cetorelli (2001). For more general reviews on the issue of banking competition see Berger et al. (1999), Carletti et al. (2002), Northcott (2004), Degryse and Ongena (2008).

of loan applicants. Manove et al. (2001) show that, in a competitive environment, the use of collateral in debt contracts may lead banks' screening effort below its socially efficient level.

De Mello (2004) analyzes a model in which the impact of bank market power on credit supply depends on how much information about borrowers is available. He provides evidence that, by increasing the rent extraction associated with acquiring private information on firms, market power induces more investment in private information acquisition, so as to recruit good borrowers. Boot and Thakor (2000) develop a banking model to study the nature of lending relationships and how these depend on competition, finding that increased bank competition improves welfare for intermediate and high quality borrowers, whereas low-quality borrowers may be either better or worse off.

Beside these studies, other works reach different conclusions. Jayaratne and Strahan (1996, 1998) find, among other things, that banks improved their screening and monitoring of borrowers after the U.S. branching deregulation. Since this latter has enhanced banking competition,[2] their results suggest indirect beneficial effects of banking competition on banks' screening activity. By using both bank level balance sheet data and macroeconomic data for the EU-15 countries, Chen (2007) finds that, after the implementation of the Second European Banking Directive, increased banking competition has improved loans' quality. Focusing on the French case, Bertrand et al. (2007) document that, following the deregulation process started in 1985 – which promoted, among other things, a more vigorous banking competition – banks improved their monitoring and/or screening functions. Chen (2005) claims that, when facing competitive pressures, it is more likely that banks choose screening activity instead of collateral requirements. Moreover, Benfratello et al. (2006) argue that higher competition can lead banks to introduce better practices in screening, selecting, evaluating and monitoring firms.

[2] On the beneficial dynamic effects of banking competition following deregulation in the U.S. see also Strahan (2003). For the Italian case, see Angelini and Cetorelli (2003).

The studies so far surveyed indicate unsettlement in the literature as to the effects of credit market structure on banks' screening activity and, through this way, on their role in allocating capital resources in the economy. This calls for further research, and the present paper aims to bring a new contribution on the topic. The empirical question we consider, along with the methodology employed, are described in the next section.

3. EMPIRICAL QUESTION AND METHODOLOGY

By employing Italian SMEs data we analyze the relationship between default probability and bank debt at firm level – evaluating whether and to what extent this link is affected by the degree of banking competition in the local credit market in which firms operate. The intuition behind this analysis is that if competition in credit markets affects banks' probability to screen, as shown by the literature on bank market structure, then (*ceteris paribus*) the effect of firms' default probability on the amount of credit granted to entrepreneurships should be different, depending on the degree of bank competition.[3] To carry out this test, we follow the empirical strategy described in the next two sub-sections.

3.1 The econometric specification

The estimating equation presents the following specification:

$$BANKDEBT_{it} = \alpha + \beta RISK + \chi HHI + \delta RISK * HHI + \phi \underline{X}_{it}^{'} + \sum_t \varphi_t T_t + \varepsilon_{it}, \qquad (1)$$

where indices *i* and *t* refer to individuals and time periods, respectively, and the dependent variable (BANKDEBT) is the ratio of bank debt to total assets. On the right hand side, RISK(1/3/5) is the

[3] As indicated in section 1, we lack information on loans interest rates at firm level, and it is for this reason that we focus only on the relationship going from SMEs' riskiness to their bank debt. Moreover, we do not have any *a priori* expectation on the sign of this relationship – being the theoretical implications of firms' characteristics on lending volumes not univocal (Stiglitz and Weiss, 1981; de Meza and Webb, 1987; Cressy, 2002).

one, three or five years firm's default probability, calculated by Moody's KMV on our sample data via *RiskCalc* model (see Section 4 for more details); HHI is the Herfindahl-Hirschman Index on deposits;[4] RISK*HHI (hereafter INTE) is the interaction term between the two variables aforementioned.[5] The vector $\underline{X}$ includes the following set of firm-specific control variables: (the log of) firm age (AGE) and its square (AGE^2); (the log of) total assets (TA) and its square (TA^2); a measure of physical capital intensity, proxied by the ratio of tangible assets to total assets (TGASS); CASH-FLOW; the ratio of liquid to total assets (LIQUI); the ratio of trade debt to total assets (TRD), as trade debt may be a substitute for bank debt (on this point see, for instance, De Blasio 2005); a group membership dummy (GROU), equal to 1 for firms belonging to a group and 0 otherwise; Pavitt dummies (PAV), to take into account heterogeneity at sectoral level. The vector $\underline{X}$ includes also two variables at provincial level: the (log of) total deposits (DEP), to control for the size of the banking market, and the ratio of bad loans to total loans (BAD) as a proxy for credit market riski-

[4] Since in Italy, like in most other European countries, data at local banking office level are not publicly available, we follow Carbò Valverde et al. (2003) and draw each variable x needed in the computation of HHI as: $x_{ipt} = X_{it} * \left(BR_{ipt} / BR_{it}\right)$, where: *i=1,…,N*; *p=1,…,103*; *t=1995,…2003*; x_{ipt} is a variable of interest for each branch office of bank *i* in province *p* in year *t*; X_{it} is the same variable of interest as it is provided by the balance sheet of bank *i* in year *t; BR_{ipt}* is the number of branch offices of bank *i* in province *p* in year *t*; BR_{it} is the total number of branch offices of bank *i* in year *t*. Then, for each year considered in the analysis, we obtain our indicator of local banking competition as follows: $HHI_p = \sum \left(ms_{ip}\right)^2$, where $ms_{ip} = \left(D_{ip} / D_p\right)$ is the market share on deposits for each branch office of bank *i* in province *p*, and $D_p = \sum_i D_{ip}$.

[5] The HHI stems from the traditional structure-conduct-performance (SCP) paradigm, which states that firms' profits are likely to be higher in more concentrated markets, where firms have greater market power and the collusion among them might be easier. This prediction has been criticized by various authors (e.g. Demsetz, 1973; Peltzman, 1977), and – with respect to the banking sector – some studies have found weak evidence in favor of a positive relationship between market concentration and profitability (e.g. Rhoades, 1995; Hannan, 1997). On the other hand, there are several contributions providing empirical support to the main argument of the SCP paradigm (e.g. Berger and Hannan, 1989; Hannan and Berger, 1991; Pilloff and Rhoades, 2002). See Gilbert (1984), Weiss (1989), and Gilbert and Zaretsky (2003) for surveys of empirical SCP studies.

ness. Finally, T_t is a set of time fixed effects, while $\varepsilon_{it} = \nu_i + u_{it}$ is a composite error, where the individual effect (ν_i) summarizes time-invariant unobserved firms' characteristics, and the second term (u_{it}) captures idiosyncratic shocks to BANKDEBT.[6] Table 1 describes all the variables employed in the estimations, while Table 2 reports their summary statistics.[7]

Focusing on the variables of interest, we specify a multiplicative interaction model, where the partial effect of RISK on BANKDEBT is conditional on the level of HHI. Formally, the marginal effect of RISK is computed as:

$$\frac{\partial BANKDEBT}{\partial RISK} = \hat{\beta} + \hat{\delta} * HHI, \tag{2}$$

where $\hat{\delta} * HHI$ is the estimated coefficient of the interaction term multiplied by the local banking competition indicator, while $\hat{\beta}$ is the estimated coefficient of RISK, indicating the marginal effect of RISK on BANKDEBT when HHI is zero. Finally, the significance of (2) is tested by calculating the relative standard error:

$$\hat{\sigma} = \sqrt{var(\hat{\beta}) + (HHI)^2 * var(\hat{\delta}) + 2HHI * cov(\hat{\beta}, \hat{\delta})}\ . \tag{3}$$

Since both (2) and (3) depend on the level of HHI, the marginal effect of RISK may change sign and gain or lose significance according to the value of the competition variable. To summarize this rich piece of information, the marginal effect of RISK will be graphed, along with its 95% confidence intervals, across the range of HHI.

[6] It is worth mentioning that a poolability test (the Breusch and Pagan Lagrange multiplier test for random effects) rejects the null hypothesis that Var(ν_i)=0. Moreover, the Hausman test rejects the null of no correlation between fixed effects and explanatory variables, and this will be taken into account in what follows.

[7] A correlation matrix is provided as an appendix.

3.2 The estimation method

As introduced above, the dependent variable is the ratio of bank loans to total assets. This variable is zero for a non-negligible proportion of the population, and is essentially continuous over positive values. In other words, there is a mass point at zero because many individuals find a corner solution optimal. In these cases, the most commonly used method is the Tobit model. The latter, however, posits a number of limitations as the same vectors of variables and coefficients determine both the probability that an observation is censored and the level of the dependent variable. In many circumstances where there are fixed costs of moving away from the mass point, this is not the case. Indeed, recent contributions on financing patterns around the world and financial relations between banks and firms assume a two-step process with regard to how firms decide their external financing sources (see, for instance, Beck et al, 2002; Hori and Osano, 2003). First, the managers choose a particular source of financing. Next, they decide the proportion of investment to finance through that source. In line with this two-step assumption, it is advocated the use of sample selection (or double hurdle) models, where the determinants of selection and amount may differ, or a given set of determinants may have different levels of relative importance.

In the present study, we test for the presence of non-random selection bias by adopting the procedure suggested by Wooldridge (1995, p. 124), which "can be viewed as an extension of Heckman's (1979) procedure to an unobserved effects framework". [8] As this test is not significant at the conventional levels, we cannot reject the null hypothesis of absence of correlation between the se-

[8] This procedure controls for unobserved heterogeneity by adopting a fixed effects (FE) model. Thus, the unobserved components are allowed to be correlated with the explanatory variables. Moreover, the idiosyncratic errors may have serial dependence of unspecified form. In our test, the selection and main equations include the same control variables with the exception of (the log of) population, the growth of real GDP (at provincial level), and the tax incentives dummy (equal to 1 if firms received tax incentives and 0 otherwise). These latter variables are assumed to affect only the selection process, and their exclusion from the main equation allows us to better identify the model. Besides, when we test this assumption by including them in both equations, their estimated coefficients are never statistically significant in the main equation.

lection and the amount processes. Hence, the latter can be estimated separately. When equation (1) is estimated by adopting a FE panel model the RISK coefficient is always positive (and statistically significant when using RISK3 and RISK5). Such a result, yet, is based on the assumption that all regressors are exogenous. However, the RISK variable (along with other explanatory variables) is likely to be endogenous. Indeed, a reverse causality may be at work: on one hand, borrowers' risk of failure is expected to influence banks' lending decisions; on the other hand, borrowers' risk can be influenced by available credit.[9] Moreover, some explanatory variables may be regarded as predetermined.[10] Furthermore, thus far we have assumed that there is no dynamic adjustment for the dependent variable. A general approach to relax these assumptions, and still control for unobserved heterogeneity, consists of two steps. Firstly, the data are transformed in order to eliminate the unobserved individual effects, and then valid instrumental variables are employed, so as to deal with the endogeneity problem posed by some regressors and the dynamic adjustment term. In the present paper, we adopt the so-called *system GMM* (*SYS-GMM*) estimator of Arellano and Bover (1995) and Blundell and Bond (1998). These authors propose a GMM procedure exploiting both the entire set of internal instruments for the model in first differences, under the assumption of white noise errors (as the *GMM-difference* estimator of Arellano and Bond, 1991), and extra orthogonality conditions for the model in levels. Such extra conditions "remain informative even for persistent se-

[9] The suspicion that RISK may be endogenous is also related to the fact that, as illustrated by Moody's KMV (2006, p. 12), a leverage variable is included in the EDF estimation. This variable is defined as (Net Worth minus Intangible Assets) to (Assets minus Intangible Assets), implying that: "large leverage corresponds to low levels of Tangible Net Worth to Tangible Assets and high default risk" (ibid: p. 12).

[10] The latter type of variables are potentially correlated with past values of the idiosyncratic error, but are not correlated to its present and future values. A strictly exogenous variable is uncorrelated with past, present and future values of the error term. In equation (1), if it appears plausible that the current value of a regressor (such as tangible assets) is influenced by past shocks to profitability, that variable is treated as predetermined. When a variable (such as RISK) is likely to be determined simultaneously along with the amount of debt, it is treated as endogenous. As a result, we treat as exogenous only Pavitt dummies and the DEP variable.

ries, and (the system estimator) has been shown to perform well in simulations" (Bond et al, 2001, p. 4), increasing the efficiency of the estimation. [11]

4. DATA

The econometric analysis is based on data coming from several sources. Information on Italian manufacturing firms is drawn from Capitalia's 7th, 8th and 9th surveys, known as *Indagini sulle Imprese Manifatturiere*, conducted on all Italian manufacturing firms employing more than 500 workers and on a stratified sample of firms with more than 10 workers. Each of these surveys, including mostly qualitative information, spans three years: the 7th survey, carried out in 1998, reports data for a panel of 4,493 firms for the period 1995-1997; the 8th one was conducted in 2001 and has data for a panel of 4,680 firms for the years 1998-2000, and the 9th, administered in 2004, includes 4,289 firms for the period 2001-2003. Capitalia provides also balance sheet data on firms included in the surveys. By matching qualitative and accounting information, we obtain an unbalanced panel of 5,998 firms for the period 1995-2003, for a total of 25,530 observations. As abovementioned, we focus on SMEs, which are bound to ask credit from banks with branches in the same local market where they operate. Therefore, we drop firms with more than 250 workers and those listed on the Stock Exchange.

A second data source is the BILBANK dataset, edited by the Italian Banking Association (ABI), which provides, for each year in the period 1995-2003, balance sheet data on nearly all Italian banks. A third dataset is provided by the Bank of Italy and gives us figures on the territorial distribution of branches for each Italian bank over the period considered in the analysis. Combining information on branches with ABI data on deposits at single bank level we have been able to implement the criterion described in sub-section 3.1 (footnote 4) to compute the HHI for each Italian

[11] More precisely, the *system GMM* estimator, along with the moment conditions of the *GMM difference*, uses the lagged differences of the regressors as instruments for the equation in levels. The main assumption underlying the use of moment restrictions in levels is that the unobserved effects are not correlated with changes in the error term.

province. It is worth noticing that aggregate deposits at provincial level (DEP) and BAD are also drawn from the Bank of Italy dataset.

Finally, as previously mentioned, data on firm riskiness come from Moody's KMV. By using the *RiskCalc* model – a rating model elaborated to forecast firms' insolvency – Moody's KMV computed the Expected Default Frequency (EDF) for the firms included in our sample. The EDF are actual firms' default probabilities and, for SMEs, are estimated relying on balance sheet and sectoral information. In the econometric analysis we employ the cumulative EDF within one, three, and five years.[12] After matching the information gathered from all the abovementioned sources, and accounting for the presence of potential outliers,[13] we obtain the estimation sample presented in Table 2.

5. RESULTS

Table 3 reports the *SYS-GMM* estimates. Column (2) shows the results obtained when the measure of prospective insolvency (RISK) indicates the default probability within one year, while the other two adjacent columns show those obtained when the insolvency measure expresses the probability that a firm goes bankrupt within three and five years, respectively. The standard errors (not reported) are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels, and the *p-values* are reported below the coefficient estimates.

Looking first at the diagnostic statistics, the autocorrelation tests signal in all regressions a strong first order correlation in the differenced residuals but no higher order autocorrelation, therefore supporting the assumption of lack of autocorrelation in the errors in levels underlying the estimator. Moreover, the Hansen test cannot reject the null hypothesis of validity of the over-identifying re-

[12] For further details on the *RiskCalc* model we refer the reader to the Moody's KMV website.

[13] For each variable involved in the econometric analysis, the observations lying in the first and last half percentile of the distribution have been dropped.

strictions, and the difference in Hansen test supports the validity of the additional instruments used by the *SYS-GMM* estimator.[14]

Focusing on the variables of interest, the RISK coefficient is always negative and statistically significant – while the INTE coefficient is all the time positive, but individually significant (at 10% level) only when the dependent variable is RISK1. Nonetheless, as shown by the F-tests reported, the interaction term is always jointly significant with the RISK regressor.[15] Therefore, the estimates in Table 3 seem to indicate that the likelihood of going bankrupt exerts a reductive effect on the amount of bank debt when the HHI is zero (and, hence, the interaction term is zero). However, since HHI is never zero in our sample, this provides us with limited information. More accurately, to analyze the marginal impact of the default probability for different levels of banking market concentration, we compute the marginal effect of RISK conditional on the value of HHI, and depict it across the entire range of the HHI by means of Figure 1.[16] Looking at this latter, the RISK variable appears to have a negative and significant impact for a large part of the HHI values: the percentage of observations falling within the region of significance is close to 60%.[17] Moreover, Figure 1 indicates that – in the statistically significant region – the estimated marginal effect of RISK on BANK-

[14] The estimates are obtained by using a subset of the available instruments. This is because, as Altonji and Segal (1994) point out, the use of all instruments implies small-sample downward bias of the coefficients and standard errors.

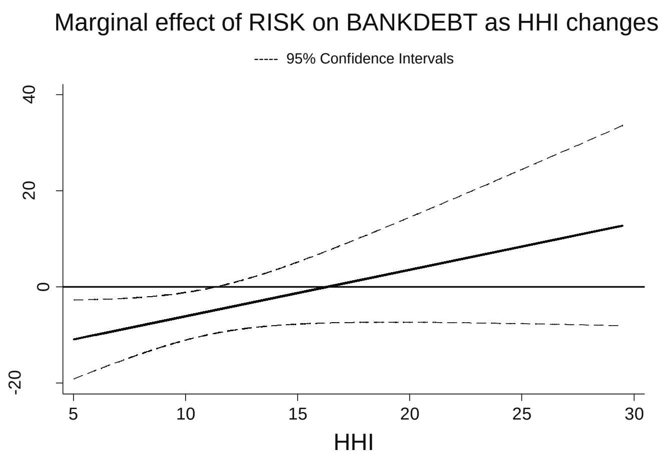
[15] The divergence between individual and joint significance may be interpreted as a symptom of multicollinearity (see Brambor et al, 2006) induced by the inclusion of the interaction term. As Brambor et al. (2006, p. 70) point out: ‘‘even if there really is high multicollinearity and this leads to large standard errors on the model parameters, it is important to remember that these standard errors are never in any sense ‘too’ large – they are always the ‘correct’ standard errors. High multicollinearity simply means that there is not enough information in the data to estimate the model parameters accurately and the standard errors rightfully reflect this’’.

[16] See sub-section 3.1 for the marginal effect and standard error formulas.

[17] As far as the not statistically significant region is concerned, the marginal effect of RISK on BANKDEBT is positive for values of HHI greater than (about) 16.5. The observations falling beyond this threshold, however, are only 7%.

DEBT decreases (in absolute value) when moving from lower to higher values of banking concentration.[18]

Figure 1



By and large, our econometric results seem to indicate that a lower (higher) local credit market concentration implies a stronger (weaker) influence of firms' riskiness on the amount of bank debt granted to SMEs. Since the relationship between firms' riskiness and bank debt is negative, *ceteris paribus*, bank financing appears to be lower (higher) for riskier SMEs running in more (less) competitive credit markets. In our view, these findings may represent evidence that a stronger bank competition could spur financial institutions to perform more accurate firms' screening. However, it is also reasonable to argue that bank financing to riskier firms could be lower in more competitive credit markets for a reason not related to bank screening: higher bank competition may erode the market power of incumbent banks, thus lowering their willingness to finance riskier firms.

[18] To economize on space, and also as they lead to the same conclusions, the graphs obtained when using the other two risk measures (RISK3 and RISK5) are omitted, but are available from the authors on request. It is worth mentioning that the only noticeable difference among the three graphs is the absolute value of the marginal effect of RISK. Indeed, the negative impact that the RISK variable exerts on BANKDEBT keeps decreasing (in absolute terms) when passing from the first measure to the last one. In other words, bank loans appear to be more affected by the probability of default within the current year, than by those within three and five years.

As claimed by an anonymous referee, the possibility that our evidence is compatible with interpretations different from the one we offer is to some extent related to the structure of the dataset employed. Indeed, while the latter provides information on the annual stock of firm's bank debt, it does not allow us to distinguish whether (and to what extent) this debt is granted by 'new banks' (meaning those which had not given credit to a firm before) or by banks having long-term relationships with firms. In deciding whether to extend or deny new credit to their borrowers, the former 'new banks' have the need to screen new borrowers, while the latter financial institutions probably rely on the outcomes of monitoring activity (rather than on a new screening process). Although the validity of this argument is fully acknowledged, we believe that there is at least one peculiarity of Italian bank-firm relationships for which the explanation of our results in terms of bank screening may be considered as plausible as the other interpretation relying on the market power of incumbent banks. We are referring to the broadly documented phenomenon of multiple banking relationships, which – even though existent in some other European countries – in Italy represents a very common feature also among medium and small entrepreneurships (see, for instance: Foglia et al, 1998; D'Auria et al, 1999; Detragiache et al, 2000; Ongena and Smith, 2000; Carmignani and Omiccioli, 2007). A likely consequence of such a widespread phenomenon might be that also firms with consolidated bank relationships could apply for credit to 'new banks' (these latter understood in the sense above indicated). If so, one cannot exclude *a priori* that many firms in our sample were addressing new banks in the period taken into account – with the possible implication that screening represented the main bank activity for the entrepreneurships we analyzed. [19]

[19] We also acknowledge that, as noted by an anonymous referee, our empirical model cannot capture the distinction between banks' *incentives* and banks' *ability* to perform screening – although, as indicated by the literature on the issue, both these aspects might be affected by credit market structure. Nonetheless, we are aware that taking into account this distinction would be relevant, both from a research perspective and in terms of policy implications. Indeed, as far as these latter are concerned, understanding which factors affect the incentives and which influence the ability of banks to screen entrepreneurships could shed new light on some important questions, as that of credit rationing to SMEs (an attempt to carry out such an analysis, by taking into account also bank monitoring, has been done by Agostino et al, 2008).

To summarize, the two interpretations so far discussed do not appear conflicting with each other; rather, it could be the case that the insights beyond both these explanations may jointly represent the source of the empirical regularity we find.

5.1 Robustness checks

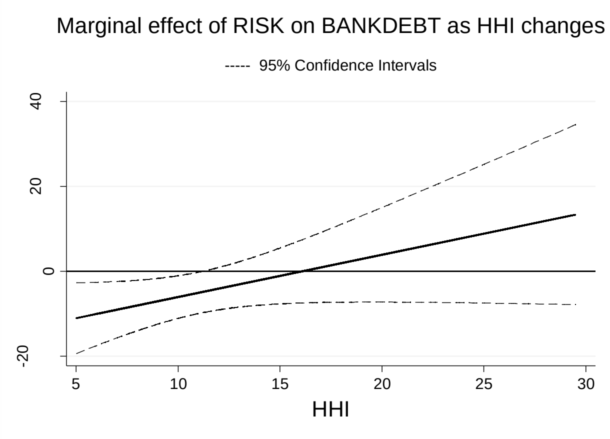
To check the robustness of the results above discussed, we have carried out several sensitivity proofs. First, equation (1) has been re-estimated by incorporating additional potential explanatory variables. To take into account effects at the macro-region level, we introduce a geographical dummy (SOUTH), which is equal to 1 if firms are located in the Southern regions of Italy and 0 otherwise. In addition, we account for some institutional and local market conditions, by adding a measure of efficiency of the judicial system (LEGENF), and a measure of the underground economy (UNDERG).[20]As shown by the results reported in columns 5-6 of Table 3, these robustness tests leave unaltered the main conclusions reached by our analysis.[21] For the sake of conciseness, we only report the following figure obtained from the results in column 6.[22]

[20] Both measures are treated as exogenous in the estimations. LEGENF is given by the backlog of civil trials pending (first degree of judgement) on population, while UNDERG is given by the irregular number of labour units on population. Data on civil trials have been drawn from ISTAT. Since they are available at judicial district level (which may include more than one province), we obtained the provincial figures by pondering with population. Data on the underground economy come from the Italian Ministry of Welfare.

[21] Our main findings are substantially confirmed also when we re-estimate equation (1) replacing DHHI with BHHI – this latter being the Herfindahl-Hirschman Index computed on bank branches at provincial level. We do not emphasize these results, however, as the Hansen is statistically significant.

[22] Columns 5 and 6 of Table 3 display the estimation results when the dependent variable of equation (1) is RISK1. The outcomes obtained when using RISK3 and RISK5 are made available upon request.

Figure 2



Following the suggestion of an anonymous referee, we have also investigated the potential non-monotonicity of the link between RISK and BANKDEBT, by re-estimating equation (1) with the square of RISK (1/3/5). The results of these further regressions, not reported and available upon request, seem to exclude the nonmonotonicity of ∂BANKDEBT/∂RISK. Indeed, the estimated coefficients of RISK and $RISK^2$ are always negative, and the latter is never individually significant.[23]

As further sensitive checks, the dependent variable of equation (1) is replaced with some measures of firm's debt growth. Since we employ a dynamic model specification, to carry out such proofs we first use LNBANKDEBT – which is the natural logarithmic of (one plus) the ratio of bank debt to total assets (BANKDEBT) – and then replace LNBANKDEBT with LNBANDEBT_L, the latter being the natural log of (one plus) firm's total bank debt in levels.[24] The results from these additional estimations, reported in Table 4 (columns 2-4 and 5-7, respectively) – and exemplified by Figures 3 and 4 – clearly provide a further confirmation of our main findings. These therefore hold when we think in terms of firms' debt growth too.[25] Evidence in favor of the foremost conclu-

[23] It is worth mentioning that the inclusion of $RISK^2$ in equation (1) requires a different formulation of (2) and (3). For further details, see the webpage related to the paper of Brambor et al. (2006), at: www.stanford.edu/~tbrambor/.

[24] Broadly speaking, when the dependent variable is taken in logarithmic form and a first lag of the same variable is included in the set of regressors (as in our case), the estimated coefficients of the latter can be interpreted as marginal effects on the rate of growth of the dependent variable (see, for instance, Oliveira and Fortunato, 2006).

[25] Figure 3 is based on column 2 of Table 4, while Figure 4 is based on column 5 of the same table.

sions of our analysis is also found when, using LNBANKDEBT or LNBANKDEBT_L as dependent variables in equation (1), this latter is augmented with the extra potential regressors indicated above in this sub-section (i.e.: AGE^2, TA^2, SOUTH, LEGENF, UNDERG).[26]

Figure 3

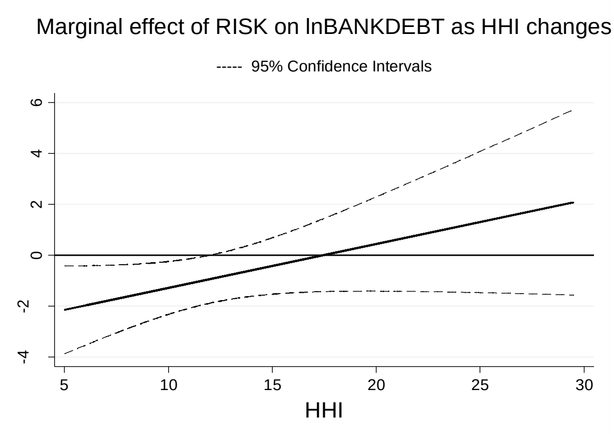
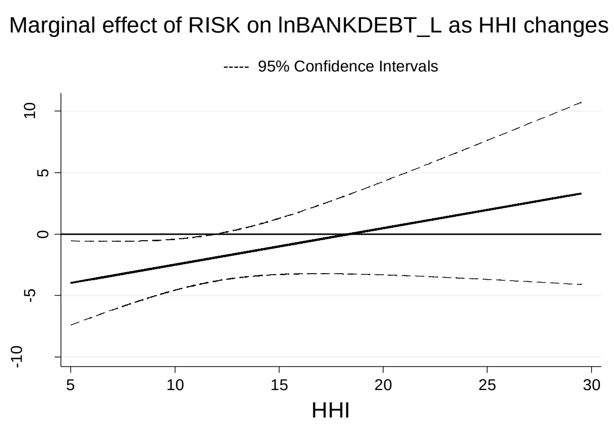


Figure 4



6. CONCLUDING REMARKS

This paper has been concerned with the role of credit market structure on banks' screening activity, a topic disputed in the literature. We have dealt with this issue by empirically investigating whether and to what extent the link between a firm's default probability and the amount of bank debt it receives is affected by the degree of competition characterizing the local credit market where the firm operates. Our approach moves from the consideration that if competition in credit markets affects banks' probability to screen, as shown by the literature on bank market structure, then (*ceteris paribus*) the effect of firms' default probability on credit quantity to entrepreneurships should be different, depending on the degree of bank competition.

The research has been conducted on a large panel of Italian SMEs for the period spanning the years from 1995 to 2003. Having focused on Italian SMEs is relevant since these firms have little

[26] These latter estimates, and the figures obtained from the results in columns 3-4 and 6-7 of Table 4, are available upon request.

access to capital markets and are bound to ask credit from banks with branches in the same local market where they operate. The methodology adopted to implement the analysis consisted in specifying a multiplicative interaction model, in which the impact of firms' riskiness profile on their usage of bank financing is made conditional on the level of local banking concentration. Moreover, both the role of firm-specific effects and the endogeneity of several determinants of bank debt have been taken into account.

Our results suggest that in local credit markets where competition is more vigorous the influence of firms' riskiness on the amount of bank debt to small and medium entrepreneurships, as well as on firms' bank debt growth, is stronger. Since the relationship between firms' riskiness and bank debt is found negative, and *ceteris paribus*, bank financing appears to be lower for riskier SMEs running in more competitive credit markets. This evidence seems to be compatible with at least two explanations. On one hand, according to some contributions (i.e. Benfratello et al, 2006), competitive pressures might stimulate banks to perform more accurate borrowers' screening, so that credit market competition would be beneficial in raising banks' efficiency in funds allocation. On the other hand, regardless of screening activity (and in line with Petersen and Rajan's, 1995 thesis), bank financing to riskier firms could be lower where credit competition is stronger because this latter might erode the market power of incumbent banks, thus reducing their incentives to finance higher riskier entrepreneurships.

We have argued that both the above interpretations may be considered likewise plausible, and not necessarily conflicting with each other, as the conceptual mechanisms they subtend may jointly represent the source of our evidence. Nonetheless, to shed more light on the issue addressed in this paper, ongoing research is devoted to explore novel empirical strategies aimed at directly relating local credit market competition with both banks' incentives and ability to screen. From this research we also expect to draw some indications that may further corroborate the policy implication suggested by the results of the present paper, namely that the profound transformation process of the

Italian banking industry – which started in the early 1990s and fostered competition in the sector (Angelini and Cetorelli, 2003) – might have improved funds allocation in the economy.

REFERENCES

Agostino, M., Silipo, D.B. and F. Trivieri. (2008) The effects of screening and monitoring on credit rationing of SMEs. *Economic Notes*, *37(2)*, 155-179.

Altonji, J. and L. Segal. (1994) Small sample bias in GMM estimation of covariance structures. NBER Working Paper,156.

Angelini, P. and N. Cetorelli. (2003) The effects of regulatory reform on competition in the banking industry. *Journal of Money Credit and Banking*, *35(5)*, 663-684.

Arellano, M. and S. Bond. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*, 277-297.

Arellano, M. and O. Bover. (1995) Another look at the instrumental variable estimation of Error Components Models. *Journal of Econometrics*, *68*, 29-51.

Beck, T., Demirgüç-Kunt, A. and V. Maksimovic. (2002) Financing patterns around the world: The role of institutions. World Bank Policy Research, Working Paper 2905.

Benfratello, L., Schiantarelli, F. and A. Sembenelli. (2006) Banks and innovation: Microeconometric evidence on Italian firms. IZA Discussion Paper 2032.

Berger, A.N. and T. Hannan. (1989) The price-concentration relationship in banking. *Review of Economics and Statistics*, *71*, 291-299.

Berger, A.N., Demsetz, R. and P. Strahan. (1999) The consolidation of the financial services industry: Causes, consequences, and implications for the future. *Journal of Banking and Finance*, *23*, 135-94.

Bertrand, M., Schoar, A. and D. Thesmar. (2007) Banking deregulation and industry structure: Evidence from the French banking reforms of 1985. *Journal of Finance*, *62(2)*, 597-628.

Blundell, R. and S. Bond. (1998) Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*, 115-143

Bonaccorsi di Patti, E. and G. Dell'Ariccia. (2004) Bank competition and firm creation. *Journal of Money, Credit and Banking, 36(2),* 225-252.

Bond, S., Temple J. and A. Hoeffler. (2001) GMM estimation of empirical growth models. Economics Papers, 21, Nuffield College, University of Oxford.

Boot, A.W.A. and A.V. Thakor. (2000) Can relationship banking survive competition?. *The Journal of Finance*, *55(2)*, 679-713.

Brambor, T., Clarck, W. and M. Golder. (2006) Understanding interaction models: Improving empirical analyses. *Political Analysis*, *14*, 63–82.

Cao, M. and S. Shi. (2001) Screening, bidding, and the loan market tightness. *European Finance Review*, *5,* 21-61.

Carbò Valverde, S., Humphrey, D.B. and F.R. Rodriguez. (2003) Deregulation, bank competition and regional growth. *Regional Studies*, *37 (3),* 227-237.

Carmignani, A. and M. Omiccioli. (2007) Costs and benefits of creditor concentration: An empirical approach. Bank of Italy, Working Paper 645.

Carletti, E., Hartmann, P. and G. Spagnolo, (2002). Implications for the bank merger wave for competition and stability. In *Risk Measurement and Systemic Risk*, Proceedings of the Third Joint Central Bank Research Conference, 38-50.

Cesarini, F. (2003) Il rapporto banca-impresa. Paper presented at the workshop *Impresa, risparmio e intermediazione finanziaria: aspetti economici e profili giuridici*, Trieste, 24-25 Ottobre 2003.

Cetorelli, N. (1997) The role of credit market competition on lending strategies and on capital accumulation. Federal Reserve Bank of Chicago, Working Paper 14.

Cetorelli, N. (2001) Competition among banks: Good or bad?. *Economic Perspectives*, *2,* 38-48.

Cetorelli, N. and P. Peretto. (2000) Oligopoly banking and capital accumulation. Federal Reserve Bank of Chicago, Working Paper 12.

Chen, X. (2005) Financial liberalization, competition, and bank loan quality. *Journal of Economic Integration*, *20*, 109-122.

Chen, X. (2007) Banking deregulation and credit risk. Evidence from the UE. *Journal of Financial Stability, 2,* 356-390.

Chiesa, G. (1998) Information production, banking industry structure and credit allocation. *Research in Economics*, *52*, 409-430.

Cressy, R. (2002) Funding gaps: A symposium. *The Economic Journal*, *112*, F1-F16.

D'Auria, C., Foglia, A. and P. Marullo Reedtz. (1999) Bank interest rate and credit relationships in Italy. *Journal of Banking and Finance*, *23*, 1067-1093.

Dell'Ariccia, G. (2000) Learning by lending, competition, and screening incentives in the banking industry. International Monetary Fund, Mimeo.

De Blasio, G. (2005) Does trade credit substitute bank credit? Evidence from firm-level data. *Economic Notes*, *34 (1)*, 85-112.

De Mello, J.M.P. (2004) Market power and availability of credit: An empirical investigation of the small firms' credit market. Stanford University, Mimeo.

Degryse, H. and S. Ongena, (2008). Competition and regulation in the banking sector: A review of the empirical evidence on the sources of bank rents. In A. Thakor and A. Boot (Eds.), *Handbook of Financial Intermediation and Banking*, Elsevier, 483-554.

Demsetz, H. (1973) Industry structure, market rivalry, and public policy. *Journal of Law and Economics*, *16*, 1-9.

Detragiache, E., Garella, P. and L. Guiso. (2000) Multiple versus single banking relationships: Theory and evidence. *Journal of Finance*, *LV (3)*, 1133-1161.

Gehrig, T. (1998) Screening, cross-border banking, and the allocation of credit. *Research in Economics*, *52*, 387-407.

Gehrig, T. and R. Stenbacka. (2001) Banking competition, financial stability, lending cycles and screening. Centre for Economic Policy Research, Discussion Paper 2915.

Gilbert, R.A. (1984) Bank market structure and competition: A survey. *Journal of Money, Credit, and Banking*, *16*, 617-645.

Gilbert, R.A. and A.M. Zaretsky. (2003) Banking antitrust: Are the assumptions still valid?. *Federal Reserve Bank of St. Louis Review*, 1-24.

Foglia, A., Laviola, S. and P. Marullo Reedtz. (1998) Multiple banking relationships and the fragility of corporate borrowers. *Journal of Banking and Finance*, *22*, 1441-1465.

Hannan, T. (1997) Market share inequality, the number of competitors, and the HHI: An examination of bank pricing. *Review of Industrial Organization*, *12*, 23-35.

Hannan, T. and A.N. Berger. (1991) The rigidity of prices: evidence from the banking industry. *American Economic Review*, *81*, 938-945.

Hauswald, R. and R. Marquez. (2006) Competition and strategic information acquisition in credit markets. *The Review of Financial Studies*, *19(3)*, 967-1000.

Heckman, J. (1979) Sample selection bias as a specification error. *Econometrica*, *47(1)*, 153-162.

Hori, K. and H. Osano. (2003) Financial relationships between banks and firms: New evidence from Japanese data. Ritsumeikan University, Mimeo

Jayaratne, J. and P.E. Strahan. (1996)The finance-growth nexus: Evidence from bank branching deregulation. *Quarterly Journal of Economics*, *111(3)*, 639-670.

Jayaratne, J. and P.E. Strahan. (1998) Entry restrictions, industry evolution and dynamic efficiency: Evidence from commercial banking. *Journal of Law and Economics*, *41*, 239-274

Manove, M., Padilla, A.J. and M. Pagano. (2001) Collateral versus project screening: A model of lazy banks. *Rand Journal of Economics*, *32*, 726-744.

Marquez, R. (2002) Competition, adverse selection, and information dispersion in the banking industry. *Review of Financial Studies*, *15*, 901-926.

de Meza, D. and D. Webb. (1987) Too much investment: A problem of asymmetric information. *Quarterly Journal of Economics*, *102*, 281-292.

Moody's KMV (2006). RiskCalc V3.1 Italy Modeling Methodology. Available at: http://v3.moodys.com/page/productsatozlist.aspx.

Northcott, C.A. (2004) Competition in banking: A review of the literature. Bank of Canada, Working Paper 24.

Oliveira, B. and A. Fortunato. (2006). Firm growth and liquidity constraints: A dynamic analysis. *Small Business Economics*, **27**, 139–156.

Ongena, S. and D.C. Smith, (2000). Bank relationship: A review. In P. Harker and S. A. Zenios (Eds.), *The Performance of Financial Institutions*, Cambridge University Press.

Peltzman, S. (1977) The gains and losses from industrial concentration. *Journal of Law and Economics*, *20*, 229-263.

Petersen, M. and R.G. Rajan. (1995) The effect of credit market competition on lending relationships. *Quarterly Journal of Economics, 110,* 407- 43.

Pilloff, S.J. and S.A. Rhoades. (2002) Structure and profitability in banking markets. *Review of Industrial Organization*, *20*, 81-98.

Rhoades, S.A. (1995) Market share inequality, the HHI, and other measures of the firm composition of a market. *Review of Industrial Organization*, *10*, 657-674.

Shaffer, S. (1998) The winner's curse in banking. *Journal of Financial Intermediation*, *7,* 359-92.

Strahan, P.E. (2003) The real effects of U.S. banking deregulation. *Federal Reserve Bank of St. Louis Review,* July/August, 111-128.

Stiglitz, J. and A. Weiss. (1981) Credit rationing in markets with imperfect information. *American Economic Review*, *71*, pp. 393–410.

Weiss, L.W, (1989). A review of concentration-price studies in banking. In L. W. Weiss (Ed.), *Concentration and Price*, Cambridge: MIT Press, 219-254.

Wooldridge, J. (1995) Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics*, *68*, 115- 132.

TABLE 1 - Description of variables used in the estimations

VARIABLE	DESCRIPTION
BANKDEBT	Bank debt to total assets
RISK1	One year firm's default probability
RISK3	Three years firm's default probability
RISK5	Five years firm's default probability
HHI	Herfindahl-Hirschman index on deposits (provincial level)
AGE *	Current year minus firm's year of establishment
TA *	Total assets
TGASS	(Property, plant, equipment and land) to total assets
CASHFLOW	(Net profit plus amounts charged off for depreciation, depletion and amortization) to total assets
LIQUI	(Cash, accounts receivable, other current assets) to total assets
TRD	Trade debt to total assets
GROU	Dummy =1 if firms belong to a group and zero otherwise
PAV1	Dummy =1 if firms belong to the traditional sectors and zero otherwise
PAV2	Dummy =1 if firms belong to the scale sectors and zero otherwise
PAV3	Dummy =1 if firms belong to the specialized supplier sectors and zero otherwise
PAV4	Dummy =1 if firms belong to the science based sectors and zero otherwise
DEP *	Total banks' deposits (provincial level)
BAD	Bad loans to total loans (provincial level)

All the variables are drawn from the 7^{th}, 8^{th} and 9^{th} Capitalia's surveys (*Indagini sulle Imprese Manufatturiere)* with the exception of: *i)* HHI, obtained by our calculations on BILBANK data; *ii)* DEP and BAD drawn from the Bank of Italy's dataset. * These variables are taken in natural logarithm in the estimations of equation (1).

TABLE 2 - Summary statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
BANKDEBT [a]	16.11	17.53	0	64.83	18016
RISK1 [a]	0.29	0.37	0.06	7.33	18016
RISK3 [a]	1.09	1.14	0.30	23.72	18016
RISK5 [a]	2.00	1.91	0.67	38.63	18016
HHI	11.29	3.76	5.01	29.49	18016
AGE [b]	23	15	1	96	18016
TA [c]	4.112	5.051	0.284	42.481	18016
TGASS [a]	22.79	15.30	0.45	71.50	18016
CASHFLOW [a]	12.98	7.55	-8.76	43.92	18016
LIQUI [a]	72.29	16.01	21.65	98.75	18016
TRD [a]	20.26	17.03	0	74.83	18016
GROU	0.185	0.389	0	1	17987
PAV1	0.521	0.500	0	1	17974
PAV2	0.187	0.390	0	1	17974
PAV3	0.255	0.436	0	1	17974
PAV4	0.037	0.189	0	1	17974
DEP [d]	7,282	11,310	177	45,706	18016
BAD [a]	6.13	5.43	1.46	45.25	18016

[a] In percentage terms; [b] in units; [c] in thousands of euro; [d] in millions of euro. The other variables are dummies, with the exception of HHI (see sub-section 3.1). For the description of the variables see Table 1.

TABLE 3 - Dynamic panel-data estimation. One-step system GMM results

	DEPENDENT VARIABLE (BANKDEBT)				
	Column 2	*Column 3*	*Column 4*	*Column 5*	*Column 6*
	RISK1	***RISK3***	***RISK5***	***RISK1***	***RISK1***
$BANKDEBT_{(-1)}$	0.652	0.656	0.657	0.652	0.653
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
RISK	-15.75	-4.704	-2.674	-15.75	-16.04
	0.018	*0.026*	*0.031*	*0.018*	*0.018*
HHI	-0.160	-0.193	-0.213	-0.161	-0.178
	0.469	*0.418*	*0.392*	*0.468*	*0.440*
INTE	0.967	0.292	0.168	0.966	0.995
	0.085	*0.096*	*0.099*	*0.086*	*0.081*
AGE	-2.952	-2.923	-2.846	-2.950	-2.730
	0.238	*0.246*	*0.260*	*0.238*	*0.276*
AGE^2	0.657	0.657	0.646	0.657	0.636
	0.127	*0.130*	*0.137*	*0.128*	*0.142*
TA	25.34	24.97	24.82	25.33	25.71
	0.010	*0.011*	*0.011*	*0.010*	*0.010*
TA^2	-1.432	-1.412	-1.403	-1.432	-1.452
	0.009	*0.010*	*0.011*	*0.009*	*0.010*
TGASS	-0.137	-0.138	-0.138	-0.137	-0.127
	0.079	*0.076*	*0.076*	*0.080*	*0.108*
CASHFLOW	-0.749	-0.745	-0.740	-0.749	-0.750
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
LIQUI	-0.229	-0.231	-0.231	-0.229	-0.218
	0.002	*0.002*	*0.002*	*0.002*	*0.004*
TRD	0.353	0.355	0.356	0.353	0.354
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
GROU	-2.323	-2.302	-2.282	-2.325	-2.316
	0.058	*0.062*	*0.065*	*0.058*	*0.063*
PAV2	6.971	7.067	7.139	6.964	7.071
	0.004	*0.003*	*0.003*	*0.004*	*0.003*
PAV3	-0.432	-0.345	-0.281	-0.458	-0.177
	0.856	*0.885*	*0.906*	*0.856*	*0.946*
PAV4	7.417	7.962	8.159	7.418	9.245
	0.155	*0.129*	*0.120*	*0.155*	*0.098*
DEP	-0.955	-0.949	-0.944	-0.957	-1.155
	0.243	*0.243*	*0.244*	*0.244*	*0.166*
BAD	-0.071	-0.067	-0.064	-0.068	-0.085
	0.230	*0.260*	*0.280*	*0.458*	*0.392*
SOUTH				-0.056	-0.994
				0.973	*0.693*
LEGENF					0.431
					0.122
UNDERG					-0.072
					0.311

continued

Table 3 continued

N.obs	8183	8183	8183	8183	8183
Model test	34.06	34.4	34.67	32.77	30.24
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
F-test joint sign (RISK, INTE)	3.61	3.09	2.8	3.61	3.58
	0.027	*0.046*	*0.061*	*0.027*	*0.028*
AB test (AR1)-FD	-11.43	-11.41	-11.4	-11.43	-11.39
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
AB test (AR2)-FD	0.20	0.22	0.23	0.20	0.22
	0.840	*0.826*	*0.820*	*0.840*	*0.829*
Hansen test	430.4	427.8	427.1	430.1	428.6
	0.134	*0.154*	*0.160*	*0.129*	*0.124*

For the description of the variables see Table 1. In Italics are reported the p-values of the tests. INTE is the interaction term between HHI and RISK 1/3/5 in columns 2-4 and between HHI and RISK 1 in columns 5 and 6. The variables AGE, TA and DEP are in natural logarithms. Constant and time dummies included but not reported. SOUTH is a territorial dummy, equal to 1 if firms belong to the Southern regions and zero otherwise; LEGENF is the backlog of civil trials pending (first degree of judgement) on population; UNDERG is the ratio of irregular number of labour units to population. The variables LEGENF and UNDERG are at provincial level, and have been obtained by our calculations on ISTAT (Italian National Institute of Statistics) and Ministry of Welfare data (see sub-section 5.1). AB test (AR1)-FD and AB test (AR2)-FD stand for Arellano-Bond test for AR in first differences and Arellano-Bond test for AR in second differences, respectively.

TABLE 4 - Robustness estimations. Changing the dependent variable

	DEPENDENT VARIABLE (LNBANKDEBT)			DEPENDENT VARIABLE (LNBANKDEBT_L)		
	Column 2	*Column 3*	*Column 4*	*Column 5*	*Column 6*	*Column 7*
	RISK1	***RISK3***	***RISK5***	***RISK1***	***RISK3***	***RISK5***
$LNBANKDEBT_{(-1)}$	0.584	0.587	0.587			
	0.000	*0.000*	*0.000*			
$LNBANKDEBT\_L_{(-1)}$				0.469	0.469	0.468
				0.000	*0.000*	*0.000*
RISK	-3.013	-0.964	-0.567	-5.462	-1.771	-1.050
	0.025	*0.021*	*0.020*	*0.041*	*0.034*	*0.032*
HHI	-0.074	-0.086	-0.093	-0.148	-0.171	-0.186
	0.037	*0.030*	*0.026*	*0.047*	*0.036*	*0.031*
INTE	0.173	0.056	0.033	0.297	0.099	0.060
	0.095	*0.079*	*0.072*	*0.154*	*0.124*	*0.111*
AGE	0.193	0.190	0.188	0.522	0.516	0.514
	0.069	*0.074*	*0.077*	*0.021*	*0.023*	*0.023*
TA	-0.284	-0.285	-0.282	0.024	0.024	0.033
	0.008	*0.009*	*0.010*	*0.931*	*0.932*	*0.909*
TGASS	0.026	0.026	0.027	0.041	0.041	0.043
	0.178	*0.172*	*0.160*	*0.316*	*0.313*	*0.297*
CASHFLOW	-0.050	-0.049	-0.048	-0.117	-0.114	-0.111
	0.005	*0.009*	*0.011*	*0.002*	*0.003*	*0.004*
LIQUI	0.003	0.003	0.004	-0.012	-0.012	-0.010
	0.873	*0.860*	*0.833*	*0.751*	*0.766*	*0.793*
TRD	0.065	0.065	0.064	0.155	0.155	0.155
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
GROU	-0.059	-0.048	-0.042	0.013	0.039	0.053
	0.667	*0.730*	*0.766*	*0.964*	*0.892*	*0.854*
PAV2	-0.050	-0.057	-0.060	-0.097	-0.112	-0.120
	0.460	*0.400*	*0.372*	*0.491*	*0.426*	*0.398*
PAV3	0.058	0.053	0.051	0.235	0.221	0.216
	0.348	*0.398*	*0.422*	*0.065*	*0.085*	*0.095*
PAV4	0.465	0.457	0.453	1.050	1.032	1.024
	0.000	*0.001*	*0.001*	*0.000*	*0.000*	*0.000*
DEP	-0.086	-0.087	-0.088	-0.127	-0.130	-0.134
	0.058	*0.060*	*0.056*	*0.232*	*0.228*	*0.214*
BAD	-0.013	-0.013	-0.012	0.011	0.013	0.014
	0.255	*0.279*	*0.291*	*0.574*	*0.522*	*0.496*
N.obs	8183	8183	8183	8183	8183	8183
Model test	27.64	27.49	27.38	34.01	33.93	33.83
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
F-test joint sign	3.21	3.24	3.21	2.93	2.91	2.90
(RISK, INTE)	*0.041*	*0.039*	*0.040*	*0.054*	*0.054*	*0.055*

continued

Table 3 continued

AB test (AR1)-FD	-8.25	-8.18	-8.13	-7.16	-7.06	-7.00
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
AB test (AR2)-FD	-0.38	-0.37	-0.37	-0.53	-0.53	-0.54
	0.704	*0.710*	*0.708*	*0.595*	*0.595*	*0.590*
Hansen test	106.8	107.6	108.0	111.1	112.7	113.4
	0.671	*0.652*	*0.641*	*0.611*	*0.571*	*0.550*

For the description of the variables see Table 1. In Italics are reported the p-values of the tests. Both the dependent variables (BANKDEBT in columns 2-4 and BANKDEBT_L in columns 5-7) are taken in natural logarithms. LNBANK-DEBT is the log of (one plus) the ratio of bank debt to total assets, while LNBANKDEBT_L is the log of (one plus) firm's total bank debt in levels. Since a lagged dependent variable is always included in the set of regressors, we can interpret the estimated coefficients of the latter as marginal effects on the rate of growth of the dependent variable,that is in terms of firms' debt growth. INTE is the interaction term between HHI and RISK 1/3/5. The variables AGE, TA and DEP are in natural logarithms. Constant and time dummies included but not reported. AB test (AR1)-FD and AB test (AR2)-FD stand for Arellano-Bond test for AR in first differences and Arellano-Bond test for AR in second differences, respectively.